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IMPLEMENTATION OF A CONJUGATE MATCHED FILTER ADAPTIVE RECEIVER FOR DS-CDMA

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Abstract

The implementation of a Conjugate Matched Filter receiver based on Adaptive Noise Cancellation (CMF-ANC) techniques for asynchronous Direct Sequence Code Division Multiple Access (DS-CDMA) mobile radio is described. The system employs a Recursive Least Squares (RLS) minimisation in the form of a modified QR-Decomposition algorithm, which is ideally suited to running on a triangular systolic array. The highly pipelined systolic array has many features which make it attractive for parallel processing architectures and Very Large Scale Integration (VLSI). Simulation results are presented for the systolic CMF-ANC receiver performance in the mobile fading environment. It is shown that the QRD-RLS version of the CMF-ANC receiver has a significantly better performance in the multiple access interference limited environment than the conventional linear correlating receiver and out-performs other adaptive strategies not based on noise cancellation techniques, such as the standard RLS algorithm. In addition, the systolic array algorithm offers greater numerical stability than the CMF-ANC receiver employing the conventional RLS adaptive solution and has a much lower computational complexity per processor.

1 Introduction

A fundamental drawback with Direct Sequence Code Division Multiple Access (DS-CDMA) mobile radio systems is the near-far problem, whereby non-zero cross-correlation between the signature waveforms of each user gives rise to Multiple Access Interference (MAI) between users. The severity of multiple access interference in DS-CDMA systems has motivated research into adaptive filtering solutions as an alternative to power control strategies for third generation mobile radio receivers. The authors have developed a novel solution to the problem of eliminating this interference in mobile DS-CDMA systems by employing adaptive interference cancellation techniques which are capable of rejecting MAI at the same time as adapting to the channel response [1, 2].

The Conjugate Matched Filter Adaptive Noise Cancellation (CMF-ANC) algorithm exploits the cyclo-stationary nature of MAI to train an adaptive filter to generate an interference replica which can then be subtracted from the received signal to provide an estimate of the desired signal. A secondary, or reference input is derived from a point in the noise field where correlation with the desired signal is very low or preferably zero. The adaptive filter attempts to model the interference transfer function between the reference and primary inputs. Adaptive noise cancellation techniques have been exploited in many fields, including communications [3]. However, they have found little application in the area of mobile DS-CDMA, primarily because of the difficulty in finding a suitable reference source which is representative of the noise in the desired signal, whilst having little or no signal content.

Crucial to the success of any algorithm for the alleviation of near-far effects in DS-CDMA is the proof that a real-time version of the scheme is indeed realisable. This paper considers how best the CMF-ANC algorithm can be modified to yield an efficient hardware implementation and provides preliminary performance results for a simulation of the proposed architecture operating in the mobile fading environment.

The ANC-CMF scheme is shown in figure 1. The primary input, comprising the desired signal and interference $s_0 + n_0$, is provided by a conventional matched filter (it is this signal on which the conventional linear correlating receiver makes a decision, to determine the received symbol). The reference signal is obtained from a Conjugate Matched Filter (CMF) which chip match filters with a signature waveform pseudo-orthogonal to all other users. This secondary signature waveform is not exploited by any other user, but is a member of the same code set. The output from the CMF can be shown to be only weakly correlated with the desired signal, but has a noise component representative of the cyclo-

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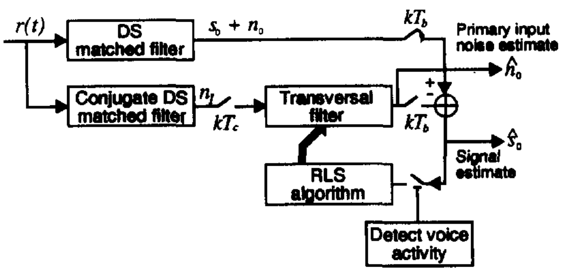

Figure 1: *CMF adaptive noise cancellation.*

stationary MAI [1]. The degree of correlation and the optimality of the solution are dependent on the orthogonality of the signature waveform set employed. The transversal filter is trained to model the transfer function between the primary and secondary inputs during periods when the desired user's signal is absent. The inherent quiet periods of voice activity are suitable for this purpose.

Adaption is achieved by minimising the Mean Squared Error (MSE) of the estimation error defined by

$$e(k) = s_0(k) + n_0(k) - \hat{n}_0(k) \quad (1)$$

$$= s_0(k) + n_0(k) - \sum_{i=1}^{m-1} \hat{w}^*(i) n_I(k-i) \quad (2)$$

where $s_0(k)$, $n_0(k)$ and $\hat{n}_0(k)$ are the desired signal, interference and filter output terms respectively for the kth iteration, $\hat{w}(i)$ is the ith tap weight estimate of the m tap transversal filter and $n_I(k-i)$ the $(k-i)$th output of the CMF. The MSE cost function is then given by

$$J(k) = E[e(k)^2] = E[s_0(k)^2] + E[(n_0(k) - \hat{n}_0(k))^2] \quad (3)$$

where E is the expectation operator. Update of the estimated tap weight vector $\hat{\mathbf{w}}(k)$, at each symbol iteration is achieved by solving the Wiener-Hopf equations

$$\hat{\mathbf{w}}(k) = \mathbf{R}^{-1}(k)\mathbf{p}(k) \quad (4)$$

where

$$\mathbf{R}(k) = \mathbf{n}_I(k)\mathbf{n}_I^H(k) \quad (5)$$

$$\mathbf{p}(k) = \mathbf{n}_I(k) n_0^*(k) \quad (6)$$

and $\mathbf{n}_I(k)$ is the m-by-1 tap input vector $[n_I(k), n_I(k-1), \ldots, n_I(k-m+1)]^T$, and H denotes the Hermitian transpose of a vector or matrix. The iterative solution of equation 4 is commonly achieved with the Recursive Least Squares (RLS) algorithm, or variants of the RLS. Although algorithms such as the RLS exhibit good convergence properties and low final error they suffer from the two shortcomings, namely, that they can become numerically unstable if the auto-correlation matrix $\mathbf{R}(k)$ is ill-conditioned and they generally do not lend themselves to efficient hardware implementations. In the following section the modified QRD-RLS algorithm is described which is numerically well behaved, even if the correlation matrix does not have full rank, and which leads to an attractive hardware realisation of the algorithm.

2 QR-Decomposition

A well documented [4, 5] approach to the least squares estimation problem which lends itself particularly well to a hardware realisation of the adaptive noise canceller is the method of orthogonal triangularisation by QR-decomposition.

A k-by-k unitary matrix $\mathbf{Q}(k)$ is defined according to

$$\mathbf{Q}(k)\mathbf{\Lambda}^{\frac{1}{2}}(k)\mathbf{X}(k) = \begin{bmatrix} \mathbf{R}_U(k) \\ \cdots \\ \mathbf{O} \end{bmatrix} \quad (7)$$

where

$$\mathbf{\Lambda}(k) = \mathrm{diag}[\lambda^{k-1}, \lambda^{k-2}, \ldots, 1] \quad (8)$$

$$\mathbf{X}(k) = \begin{bmatrix} n_I(1) & n_I(2) & \cdots & n_I(k) \\ n_I(0) & n_I(1) & \cdots & n_I(k-1) \\ \vdots & \vdots & \ddots & \vdots \\ n_I(2-m) & n_I(3-m) & \cdots & n_I(k-m+1) \end{bmatrix} \quad (9)$$

and $\mathbf{R}_U(k)$ is an m-by-m upper triangular matrix. The diagonal matrix $\mathbf{\Lambda}(k)$ has the effect of decreasing the contribution of older data samples to the algorithm update and thereby permits adaption to non-stationary channels, through the choice of *forgetting factor* λ. If the primary data vector is defined as

$$\mathbf{d}^H = [s_0(1) + n_0(1), s_0(2) + n_0(2), \ldots, s_0(k) + n_0(k)] \quad (10)$$

then the k-by-1 error vector $\mathbf{e}(k)$, is given by

$$\mathbf{e}(k) = \mathbf{X}(k)\mathbf{w}(k) + \mathbf{d}(k) \quad (11)$$

from equations 7 and 11

$$\mathbf{Q}(k)\mathbf{\Lambda}^{\frac{1}{2}}(k)\mathbf{e}(k) = \begin{bmatrix} \mathbf{R}_U(k) \\ \cdots \\ \mathbf{O} \end{bmatrix} \mathbf{w}(k) + \begin{bmatrix} \mathbf{p}(k) \\ \cdots \\ \mathbf{v}(k) \end{bmatrix} \quad (12)$$

where

$$\begin{bmatrix} \mathbf{p}(k) \\ \cdots \\ \mathbf{v}(k) \end{bmatrix} \equiv \mathbf{Q}(k)\mathbf{\Lambda}^{\frac{1}{2}}(k)\mathbf{d}(k) \quad (13)$$

$\mathbf{p}(k)$ is defined to be an m-by-1 vector to maintain dimensional consistency in equation 12. As $\mathbf{Q}(k)$ is a unitary, orthogonal matrix the vector form of the MSE cost function of equation 3 can be expressed as

$$\mathbf{J}(k) = \| \mathbf{\Lambda}^{\frac{1}{2}}(k)\mathbf{e}(k) \| = \| \mathbf{Q}(k)\mathbf{\Lambda}^{\frac{1}{2}}(k)\mathbf{e}(k) \| \quad (14)$$

$$= \left\| \begin{bmatrix} \mathbf{R}_U(k) \\ \cdots \\ \mathbf{O} \end{bmatrix} \mathbf{w}(k) + \begin{bmatrix} \mathbf{p}(k) \\ \cdots \\ \mathbf{v}(k) \end{bmatrix} \right\| \quad (15)$$

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The least squares estimate for the tap weight vector is obtained from equation 15 when

$$\mathbf{R}_U(k)\mathbf{w}(k) + \mathbf{p}(k) = 0 \tag{16}$$

The upper triangular matrix $\mathbf{R}_U(k)$ is recursively updated at each symbol iteration by applying a sequence of Givens rotations according to:

$$\begin{bmatrix} \mathbf{R}_U(k) \\ \cdots \\ \mathbf{O} \\ \mathbf{0}_m^T \end{bmatrix} = \mathbf{\Gamma}(k) \begin{bmatrix} \lambda^{1/2}\mathbf{R}_U(k-1) \\ \cdots \\ \mathbf{O} \\ \mathbf{n}_I^H(k) \end{bmatrix} \tag{17}$$

where $\mathbf{\Gamma}(k)$ denotes the sequence of Givens rotations $\mathbf{G}_m(k)\cdots\mathbf{G}_2(k)\mathbf{G}_1(k)$. The successive application of the Givens rotations serves to annihilate all of the non-zero elements in the bottom row of the right hand matrix of equation 17. Specifically, if a matrix is denoted by $\mathbf{Z}$ then the element z_{ij} (the jth element on row i) can be annihilated if the rotation parameters c and s are chosen such that

$$c = \frac{|z_{jj}|}{\sqrt{|z_{jj}|^2 + |z_{ij}|^2}} \tag{18}$$

$$s = \frac{z_{ij}}{z_{jj}}c \tag{19}$$

The matrix $\mathbf{Q}(k)$ is also recursively updated from $\mathbf{Q}(k-1)$ using the Givens rotation sequence as each new set of data enters the computation

$$\mathbf{Q}(k) = \mathbf{\Gamma}(k) \begin{bmatrix} \mathbf{Q}(k-1) & \vdots & \mathbf{0}_{k-1} \\ \cdots & \vdots & \cdots \\ \mathbf{0}_{k-1}^T & \vdots & 1 \end{bmatrix} \tag{20}$$

As $\mathbf{R}_U(k)$ is an upper triangular matrix equation 16 can be solved for the weight vector $\mathbf{w}(k)$, by back substitution. However, in adaptive noise cancellation applications such as that proposed in this paper it is often not necessary to calculate the weight vector explicitly, and in fact the *a posteriori* error (equivalent to the signal estimate in this application) can be calculated directly from two quantities which are relatively easily available within the QRD algorithm [6]:

$$e(k) = \gamma(k)\alpha(k) \tag{21}$$

where

$$\gamma^{\frac{1}{2}}(k) = \prod_{i=1}^{m} c_i(k) \tag{22}$$

and $\alpha(k)$ is the *a priori* error given by

$$\alpha(k) = d(k) - \lambda^{\frac{1}{2}}\mathbf{p}^H(k-1)\beta(k) \tag{23}$$

and $\beta(k)$ is an m-by-1 vector defined by

$$\beta(k) = \gamma^{-\frac{1}{2}}(k) \begin{bmatrix} s_1^*(k)c_2(k)c_3(k)\cdots c_m(k) \\ s_2^*(k)c_3(k)\cdots c_m(k) \\ \vdots \\ s_m^*(k) \end{bmatrix} \tag{24}$$

The calculation of the *a posteriori* error directly from the two quantities $\gamma(k)$ and $\alpha(k)$ without the requirement for the inversion of the correlation matrix $\mathbf{R}_U(k)$ is an important result as the inversion procedure is potentially numerically unstable, whereas the values of $\gamma(k)$ and $\alpha(k)$ are always well defined. If the data matrix is ill-conditioned, or in the worst case has a rank less than m, the conventional RLS algorithm will rapidly become numerically unstable as the inversion of $\mathbf{R}_U(k)$ becomes impossible, whereas, for the modified QRD algorithm $\gamma(k)$ and $\alpha(k)$ are still defined.

3 The Modified Systolic Array

The modified QRD-RLS algorithm was implemented as the systolic array [7, 8, 9] shown in figure 2. Suitably delayed samples of the reference signal are clocked through the upper triangular portion of the array at the symbol rate, while the primary signal is clocked through the bottom row of the array. Although the update of the array is carried out out the symbol period the temporal spacing between adjacent elements of the array is offset by a chip period to facilitate characterisation of the MAI. The triangular array is centered on the user timing point with preceding rows being delayed by a chip period and following rows advanced by a chip period, as denoted by the reference signal subscripts of figure 2. The equivalent transversal filter architecture is the m-tap chip-spaced delayline.

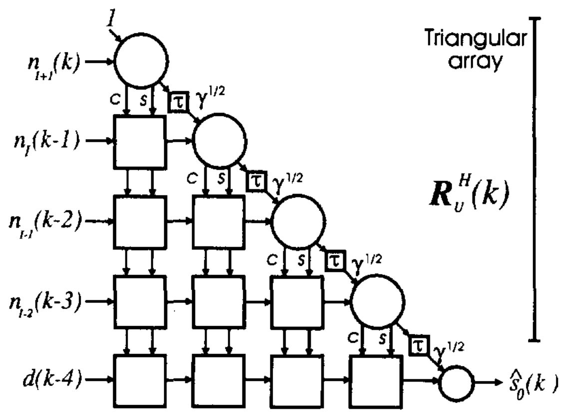

Figure 2: *The modified QRD-RLS algorithm implemented as a systolic array of order* $m = 4$.

The array comprises three types of processing elements; boundary cells, internal cells and a final processing cell (denoted by circles, squares and a small circle respectively in figure 2). Each element of the triangular portion of the array has an associated internal state r_{ij}, which is equivalent to the corresponding element of the lower triangular correlation matrix $\mathbf{R}_U^H(k)$. Simi-

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larly, the state values of the bottom row of the array describe the vector $\mathbf{p}^H(k)$. The boundary cells compute the Givens rotation parameters $c(k)$ and $s(k)$, product term $\gamma^{\frac{1}{2}}$, and update their state at each iteration according to [5]

$$\begin{aligned} r'_{ij} &\leftarrow \sqrt{\lambda r_{ij}^2 + |n_{in}|^2} \\ c &\leftarrow \frac{\lambda^{\frac{1}{2}} r_{ij}}{r'_{ij}} \\ s &\leftarrow \frac{n_I}{r'_{ij}} \\ r_{ij} &\leftarrow r'_{ij} \\ \gamma_{\text{out}}^{\frac{1}{2}} &\leftarrow c\gamma_{\text{in}}^{\frac{1}{2}} \end{aligned} \tag{25}$$

The boundary cells also serve to delay the output of $\gamma^{\frac{1}{2}}$ by one clock cycle to compensate for the skew of data in the matrix. The internal cell operation is described by

$$\begin{aligned} n_{\text{out}} &\leftarrow cn_{\text{in}} - s^* \lambda^{\frac{1}{2}} p_{ij} \\ p_{ij} &\leftarrow sn_{\text{in}} + c\lambda^{\frac{1}{2}} p_{ij} \end{aligned} \tag{26}$$

and the final processing cell computes the *a posteriori* error according to

$$n_{out} \leftarrow \gamma^{\frac{1}{2}} n_{in} \tag{27}$$

The system is only allowed to adapt when the desired signal is known to be absent to satisfy the criteria that no component of desired user's signal is present in the reference signal during adaption. At other times the state of the systolic array is 'frozen' and the *a posteriori* error computed on the basis of the state and rotation parameters held in the bottom row of the array.

Initialisation of the array is carried out by assuming pre-windowing of all data (i.e. all data for $k < 0$ assumed zero) and by setting $\mathbf{R}_U(0) = \mathbf{0}$ and $\mathbf{p}(0) = \mathbf{0}$. The Givens rotation parameters c and s take the values 1 and 0 respectively at $k = 0$. As the channel and user configuration are non-stationary the array is also re-initialised at the start of each new adaption period.

From inspection of equations 25 to 27 the greatest processing overhead is associated with the calculations performed by the boundary cells at each iteration. Therefore, the requirement for real-time operation of the array is that the boundary cell operations must be performed within a single iteration period, which is comparatively easy to achieve as the array is designed to be clocked at the symbol rate, rather than the code chipping rate. The array has a latency of m symbol periods which arises from the requirement to clock the data through the processing elements, but, provided the model order is not too high, the delay can be tolerated in this application.

An advantage of the systolic array over other architectures is that the individual processing element computational burden does not grow with increasing order m. Therefore, assuming the target hardware is capable of supporting the required number of processing elements, larger filter orders can be accommodated than with contemporary algorithms such as the standard RLS which has a computational complexity of $O(m^2)$.

4 Simulation Results

The ANC-CMF receiver has been implemented as a systolic array employing the modified QRD-RLS algorithm detailed above, using hardware based on a TMS320C30 digital signal processor. The mobile multiuser Rayleigh fading channel at 900MHz is simulated on a network of workstations and the CMF receiver applied to the compound channel output. Preliminary results for the bit error rate performance of the CMF-ANC algorithm for varying numbers of users are shown in figure 3. Results for the Conventional Linear Correlating Receiver (CLCR) and a conventional RLS algorithm are also given for comparison. The RLS algorithm employed a chip-spaced transversal filter operating on the output from the desired user's matched filter, with adaption achieved using a pre-determined pseudo-random code sequence. The CMF uses a reserved code from the set of 63 chip Gold code signature waveforms utilised by all other users. For both the CMF-ANC and RLS schemes the value of *forgetting factor* was chosen to optimise adaption to the non-stationary channel. Typically this results in a choice of $\lambda \approx 0.96$.

The *near-far* performance of the QRD-RLS algorithm is shown in figure 4 for the comparatively severe MAI case of 11 users. The Signal to Interference Ratio (SIR) denotes the ratio of the desired user mean signal level to that of all other users. Again, results for the RLS and CLCR receivers are shown for comparison.

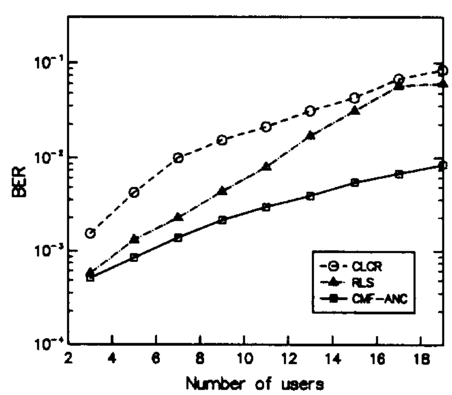

Figure 3: *BER performance comparison of the QRD systolic array at 20dB SNR.*

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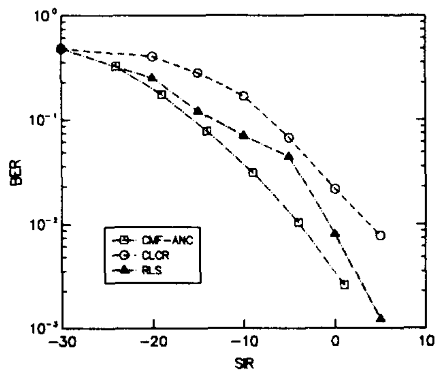

Figure 4: *Near-far performance comparison of the QRD-RLS algorithm for 11 users at 20dB SNR.*

5 Discussion

Figure 3 shows that BER performance for the CMF-ANC receiver is significantly better than that of the CLCR, with up to an order of magnitude improvement at higher levels of MAI. For the RLS system performance is comparable with the CMF-ANC receiver at lower user numbers, but approaches that of the CLCR at higher interference levels. It is thought that this degradation in RLS performance arises through the filter order being too small to effectively characterise the MAI at higher user numbers. Although the CMF-ANC scheme suffers from this problem to some extent, it is better able to characterise the MAI.

Figure 4 demonstrates that the *near-far* resistance of the CMF-ANC receiver employing the QRD-RLS algorithm is considerably better than the CLCR and basic RLS receivers. At moderate levels of SIR performance is almost an order of magnitude better than the CLCR.

6 Conclusions

The implementation of a CMF-ANC receiver for mobile DS-CDMA as a modified systolic array has been presented. The systolic array, when used in an adaptive noise cancellation application such as this, has the advantage over other architectures that direct computation of the filter tap weight vector is not required as the desired signal estimate can be computed from array parameters. In addition, the computational complexity of each processing element of the array is fixed, irrespective of the model order. These factors reduce the array complexity and computational burden considerably. Use of the QRD-RLS algorithm ensures a greater degree of numerical stability than the standard RLS scheme, as the algorithm is still stable if the linear system is ill conditioned.

BER performance for the systolic CMF-ANC receiver in the MAI limited environment is significantly better than that of the conventional linear correlating receiver and superior to contemporary adaptive filtering solutions such as the RLS.

7 Acknowledgments

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